DETERMINING ECONOMIC DAMAGES WHEN FOOD AND BEVERAGE PRODUCTS ARE MISLABELED

A Thesis

by

MICHAEL THOMAS NEPVEUX

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Chair of Committee,	Oral Capps, Jr.
Committee Members,	Senarath Dharmasena
	Ariun Ishdorj
Head of Department,	C. Parr Rosson III

December 2015

Major Subject: Agricultural Economics

ABSTRACT

In recent years, the number of consumer class actions brought against manufacturers of retail products has been on the rise particularly with respect to labeling claims such as “No Sugar Added”, “All Natural”, or “Zero Grams Trans Fat.” This thesis establishes a methodology to be used in the calculation of damages due consumers as the result of misstated or misleading labeling claims on food and beverage products. The core of this methodology rests on the use of hedonic regression analysis to determine the existence and amount of any price premiums resulting from the specific labeling claims at issue. Hedonic price analysis is widely accepted within the economic literature, and in a recent number of food labeling class action lawsuits, the use of the hedonic technique has been put forth to attempt to extract price premiums. In this light, the objectives of this thesis are to: (1) determine the potential premium paid by consumers as a result of any misbranded or misleading label claim; and (2) calculate the extent of ill-gotten profits received by food and beverage manufacturers based on this estimated premium. This methodology establishes the basis of disgorgement, a damages measure defined as the return of the money received by food and beverage manufacturers from the sale of misbranded products to consumers.

In addressing these objectives, a “case study” example is employed using a hypothetical lawsuit to demonstrate the methodology proposed. The product of focus in the case study is ready-to-drink cranberry juice, and the label claim is “No Sugar Added”. In order to determine the premium paid by consumers, a hedonic regression

model is constructed with price expressed as a function of a set of various product attributes as well as other explanatory factors. Once the premium is obtained, the extent of disgorgement is determined.

Based on the hedonic price analysis, in this hypothetical case, the “No Sugar Added” claim resulted in a 25.35% premium paid by consumers. From this premium, the manufacturer of the brand with the alleged mislabeling claim could have been held liable for damages in the range of approximately $102 million to $117 million. The methodology employed in this case study can be extended to any class action lawsuit featuring the misbranding or mislabeling of food and beverage products.

ACKNOWLEDGEMENTS

I would like to thank my committee chair and inspiring mentor, Dr. Oral Capps, Jr. for his many hours of teaching, guidance, and support throughout both my graduate and undergraduate career, and without whose support I would not be where I am today. I would also like to thank my committee members, Dr. Senarath Dharmasena and Dr. Ariun Ishdorj for their guidance and support throughout the course of this research as well as their teaching and advice throughout my graduate career.

Additionally, I would like to thank my colleague Nima Khodakarami, who when taking breaks from studying for his qualifier, would take the time to help me with data compilation. I would also like to thank my colleague Alec Bardzik, who, having already overcome many similar issues dealing with the Nielsen data, would share his experience and advice to make my research go much smoother than it could have.

Thanks also go to my friends and colleagues, and the Department, faculty, and staff for making my time at Texas A&M University a great experience. Finally, thanks to my family and Allison for their endless encouragement, patience, and support.

NOMENCLATURE

FDA	Food and Drug Administration
FD&C Act	Federal Food, Drug, and Cosmetic Act
NLEA	Nutrition Labeling and Education Act
CFR	Code of Federal Regulations
NSA	No Sugar Added
FOP	Front of Package
NCC	Nutrient Content Claim

TABLE OF CONTENTS

Page

LIST OF FIGURES

Page

LIST OF TABLES

CHAPTER I

INTRODUCTION

Manufacturers of food and beverage products constantly seek to differentiate their products from others in the eyes of the consumer. Producers can accomplish this goal in a variety of ways, including but not limited to shelf placement, advertising, and, most importantly, product packaging and labeling. Consumers often utilize labels on product packaging to assist them in making their purchase decisions. These labeling statements must adhere to a range of federal and state regulations to ensure that the information reported is true and accurate, therefore not misleading the consumer. When companies fail to meet these requirements, they may be subject to class action lawsuits from consumers who seek compensation for purchasing a product attributed to a misstated or misleading label.

In recent years, the number of consumer class actions brought against manufacturers of retail products has been on the rise particularly with respect to labeling claims (Jain, 2015) such as “No Sugar Added”, “All Natural”, or “Zero Grams Trans Fat.” This thesis establishes a methodology to be used in the calculation of damages due consumers as the result of misstated or misleading labeling claims on food and beverage products. The core of this methodology rests on the use of hedonic regression analysis to determine the existence and amount of any price premiums resulting from the specific labeling claims at issue. Hedonic price analysis is widely accepted within the economic literature, and in a recent number of food labeling class action lawsuits, the use of the hedonic technique has been put forth to attempt to extract price premiums. In this light, the objectives of this thesis are to: (1) determine the potential premium paid by consumers as a result of any misbranded or misleading label claim; and (2) calculate the extent of ill-gotten profits received by food and beverage manufacturers based on this estimated premium. This methodology establishes the basis of disgorgement, a measure of damages defined as the return of the money received by food and beverage manufacturers from the sale of misbranded products to consumers.

Initially, attention is centered on the methodology used to achieve the objectives, namely, hedonic price analysis. This methodology is then used in an example to illustrate the process. The example employed subsequently is a hypothetical case which establishes that a manufacturer had allegedly included a "No Sugar Added" labeling claim that was misleading and in violation of Federal and state law. This hypothetical case is utilized as an example of how the methodology proposed could be implemented in similar cases moving forward.

Literature Review

The purpose of reviewing past and current literature is to demonstrate the importance that consumers place on food labels to convey product information. Further, the literature review serves to give background on the applicability of the proposed methodology, namely the use of hedonic price analysis. Additionally, the methodology section establishes sufficient precedent in the use of the hedonic price functions for this study.

Use of Food Labels by Consumers

A wide range of scientifically-based surveys and academic papers purport that product labels are substantial factors in consumers' decision to purchase food and beverage products. In 2008, the Food and Drug Administration (FDA) conducted a telephone survey of 2,584 non-institutionalized adults (age 18+) using a nationally representative sample of telephone numbers. This survey found that when buying a product for the first time, 77% of the respondents often or sometimes read the labels on food products that list ingredients as well as nutritional and other information. When comparing different food items with each other 75% of respondents often or sometimes utilize the labels, and in deciding between brands of a specific food item to purchase, 73% of the respondents often or sometimes use this information. In obtaining a general idea of the nutritional content of the food 85% of respondents often or sometimes use the label, and when specifically looking at how high or low the product is in items such as calories, salt, fat, etc., 90% of the survey's respondents said that they use the products label. Finally, when a food or beverage product has a statement on the front of the package describing the amount of certain nutrients in the product (low fat, cholesterol-free, high fiber, etc.), 72% of the respondents often or sometimes use these front-of-package (FOP) statements in their purchase decision (Choiniere and Lando, 2010).

The implementation in 1994 of the Nutrition Labeling and Education Act (NLEA) led to a multitude of studies attempting to understand how food labeling information affects consumer purchasing decisions. In developing packaging for food and beverage products, manufactures face an incentive to develop labels and labeling statements about their products' nutritional attributes if they believe consumers will pay more for the benefits associated with these claims. Studies have shown that consumers utilize labeling information in their purchasing decisions, and that they are usually willing to pay a premium for foods with specific characteristics (Muth et al. 2013). Many times these labeling statements are meant to signal positive nutritional benefits to be gained in the consumption of their products, and are considered credence attributes as a consumer is not aware of these benefits in the absence of any statement (Muth et al. 2013).

In addition to signaling the presence of positive nutritional attributes, labels often also advertise the absence of negative nutritional attributes. Consumers may be more concerned about negative elements present in a product such as calories, cholesterol, sugar, and sodium. Sometimes consumers look to labels for information on the inclusion of these negative attributes more so than looking for the presence of positive attributes such as protein, iron, and calcium (Russo et al. 1986). Additionally, Balasubramanian and Cole (2002) investigated the effects of the NLEA, and found that its implementation resulted in increased consumer sensitivity to foods possessing labeling that emphasized the lack of these negative attributes relative to the statements about the positive nutritional attributes of the product. Also in investigating the effects of the NLEA, Kim, Nayga, and Capps (2000) conducted research on the effect of food label use on the nutrient intake of consumers. They found that utilizing labels concerning nutrition led to a decrease in the intake of the negative nutrients such as total fat, saturated fat, by 6.9% and 2.1%, and cholesterol and sodium by 67.6 milligrams, and 29.58 milligrams.

Food Labeling Policy

The Food and Drug Administration (FDA) bears the responsibility of assuring that foods sold in the United States are properly labeled. The Federal law mandating this assurance is the Federal Food, Drug, and Cosmetic Act (FD&C Act), established in 1938. In 1990, the NLEA amended the FD&C Act requiring foods to contain nutrition labels and for food labels that contain certain health messages such as nutrient content claims to comply with specific requirements (FDA 2013). These specific requirements are updated regularly, and these newly updated regulations are published in the Federal Register as well as listed in Title 21 of the Code of Federal Regulations (CFR) on an annual basis (FDA 2013).

In the design of their product packaging, food and beverage manufacturers may display additional health claims, nutrient content claims (NCCs), and related statements on the packaging to highlight the nutritional aspects of their product (FDA 2013), but these claims must comply with requirements laid out in the CFR. These statements are often located on the front of the packaging and are referred to Front of Package (FOP) labeling. NCCs are claims on the products that directly or by implication characterize the level of a nutrient in the food and can be either expressed nutrient content claims or implied nutrient content claims (FDA 2013). The CFR defines an expressed nutrient content claim as "any direct statement about the level (or range) of a nutrient in the food, e.g., 'low sodium' or 'contains 100 calories'" (21CFR101.13). CFR defines an implied nutrient content claim as a claim that "describes the food or an ingredient therein in a manner that suggests that a nutrient is absent or present in a certain amount (e.g., 'high in oat bran')" (21CFR101.13), or a claim that implies the product may be useful in maintaining a healthy diet while made in conjunction with an explicit claim.

Additionally, labeling regulations in the CFR define what terms may be used to describe nutrient content in food and in what ways they may be used. Some recognized content claims include adjectives such as free, low, and reduced/less, and can be applied to nutrients such as sodium, total fat, calories, and sugar among others (FDA 2013). For example, in order to contain the label "Sugar Free", the product must contain less than 0.5 g of sugars per labeled serving. The specific claim "No Sugar Added" (NSA) is included under the following CFR rule:

> The terms "no added sugar," "without added sugar," or "no sugar added" may be used only if:
>
> (i) No amount of sugars, as defined in 101.9(c)(6)(ii), or any other ingredient that contains sugars that functionally substitute for added sugars is added during processing or packaging; and
>
> (ii) The product does not contain an ingredient containing added sugars such as jam, jelly, or concentrated fruit juice; and
>
> (iii) The sugars content has not been increased above the amount present in the ingredients by some means such as the use of enzymes, except where the intended functional effect of the process is not to increase the sugars content of a food, and a functionally insignificant increase in sugars results; and
>
> (iv) The food that it resembles and for which it substitutes normally contains added sugars; and
>
> (v) The product bears a statement that the food is not "low calorie" or "calorie reduced" (unless the food meets the requirements for a "low" or "reduced calorie" food) and that directs consumers' attention to the nutrition panel for further information on sugar and calorie content.

(21CFR101.60)

The FDA also understood the rising adoption and importance of FOP labeling, so it issued a letter to food and beverage manufacturers in 2009 (see Figure 1 and Figure 2). FDA's research found that due to FOP labeling, consumers were less likely to read the Nutrition Facts label of the product. This finding increased the need that FOP labeling be fully accurate and not mislead the consumer on the merits of the product (FDA 2009).

Figure 1: 2009 FDA Letter to Industry

Dear Industry:

Point of purchase labeling including Front of Package (FOP) labeling is voluntary information that is intended to convey to consumers the nutritional attributes of a food. Point of purchase labeling often includes symbols that are typically linked to a set of nutritional criteria developed by food manufacturers, grocery stores, trade organizations, and health organizations. Two major categories of FOP symbol systems are "summary" and "nutrient-specific" systems. The summary symbols use logos, numerical scores, or graphic schemes to communicate the overall nutritional quality of a food product to consumers and facilitate comparisons between products based on the food's nutritional quality. Nutrient-specific symbols provide quantitative, evaluative, or both kinds of information on selected nutrients in a product without comparing the product's overall nutritional quality to that of its counterparts.

Although all symbol programs intend to indicate that the food products with their symbol are healthful choices, each symbol program has different nutritional criteria. The selected nutrients and the nutrient levels required for eligibility vary among the different symbol programs in use. FDA recognizes that point of purchase labeling can be a way of promoting informed food choices and helping consumers construct healthier diets in accordance with the Dietary Guidelines for Americans. FOP or shelf labeling that provides consumers with readily accessible information about a product's nutritional profile, in a manner that is consistent with and linked to the required Nutrition Facts panel, responds to today's marketplace realities and can be part of the education and outreach consumers need to understand and act on nutrition information at the point of purchase.

However, FDA's research has found that with FOP labeling, people are less likely to check the Nutrition Facts label on the information panel of foods (usually, the back or side of the package). It is thus essential that both the criteria and symbols used in front-

Figure 1 continued

of-package and shelf-labeling systems be nutritionally sound, well-designed to help consumers make informed and healthy food choices, and not be false or misleading. The agency is currently analyzing FOP labels that appear to be misleading. The agency is also looking for symbols that either expressly or by implication are nutrient content claims. We are assessing the criteria established by food manufacturers for such symbols and comparing them to our regulatory criteria.

It is important to note that nutrition-related FOP and shelf labeling, while currently voluntary, is subject to the provisions of the Federal Food, Drug, and Cosmetic Act that prohibit false or misleading claims and restrict nutrient content claims to those defined in FDA regulations. Therefore, FOP and shelf labeling that is used in a manner that is false or misleading misbrands the products it accompanies. Similarly, a food that bears FOP or shelf labeling with a nutrient content claim that does not comply with the regulatory criteria for the claim as defined in Title 21 Code of Federal Regulations (CFR) 101.13 and Subpart D of Part 101 is misbranded. We will consider enforcement actions against clear violations of these established labeling requirements.

FDA is also developing a proposed regulation that would define the nutritional criteria that would have to be met by manufacturers making broad FOP or shelf label claims concerning the nutritional quality of a food, whether the claim is made in text or in symbols. FDA's intent is to provide standardized, science-based criteria on which FOP nutrition labeling must be based.

We also intend to continue to improve our understanding of how consumers view and use such labels. Research suggests that the proliferation of divergent FOP approaches is likely to be confusing to consumers and ultimately counter-productive. We want to work with the food industry - retailers and manufacturers alike - as well as nutrition and design experts and the Institute of Medicine, to develop an optimal, common approach to nutrition-related FOP and shelf labeling that all Americans can trust and use to build better diets and improve their health.

The recent experience with FOP labeling in the United Kingdom demonstrates the potential of voluntary initiatives to provide consumers helpful FOP labeling. In that instance, the government set certain criteria for the use of such labeling, and retailers took the initiative to implement FOP labeling in their stores. The agency wants to explore the potential of that approach. If voluntary action by the food industry does not result in a common, credible approach to FOP and shelf labeling, we will consider using our regulatory tools toward that end. This effort will include research to assess through consumer studies the likely effects of FOP symbols on information search behavior related to the Nutrition Facts label, which in turn can affect consumer understanding of

Figure 1 continued

the full nutrition profile of a product. The foundation of that approach should be a common set of mandatory nutritional criteria that consumers can rely on when they view FOP labels, even if no one symbol is ultimately selected as superior.

Accurate food labeling information can assist consumers in making healthy nutritional choices. FDA intends to monitor and evaluate the various FOP labeling systems and their effect on consumers' food choices and perceptions. FDA recommends that manufacturers and distributors of food products that include FOP labeling ensure that the label statements are consistent with FDA laws and regulations. FDA will proceed with enforcement action against products that bear FOP labeling that are explicit or implied nutrient content claims and that are not consistent with current nutrient content claim requirements. FDA will also proceed with enforcement action where such FOP labeling or labeling systems are used in a manner that is false or misleading.

FDA intends to work in collaboration with our sister public health agencies and the Department of Agriculture, which has authority over the labeling of meat and poultry, to pursue these efforts on FOP labeling. We will base our initiative on sound consumer research to ensure that we move toward an approach that will help consumers in selecting a healthy diet.

Sincerely,

Barbara O. Schneeman, Ph.D.
Director
Office of Nutrition, Labeling and Dietary Supplements
Center for Food Safety and Applied Nutrition
Food and Drug Administration

Figure 2: 2007 FDA Letter to Industry

Dear Manufacturer:

The Food and Drug Administration (FDA) is concerned about the number of products we have seen that contain claims regarding the absence of sugar, such as, "sugar free" but that fail to bear the required disclaimer statement when these foods are not "low" or "reduced in" calories or fail to bear the required disclaimer statement in the location or with the conspicuousness required by regulation. As part of our continuing effort to reduce the incidence of obesity in the United States, FDA wants to ensure that consumers are provided with the label information they need to make informed choices for maintaining a healthy diet. We are highlighting accurate claims about the absence of sugar as a regulatory priority. The agency intends to take appropriate action against products that we encounter that bear a claim about the absence of sugar (e.g., sugar free) but that fail to meet each of the requirements of the regulation that defines "sugar free." We intend to pay particular attention to those foods that are required to bear a disclaimer statement under the regulation that defines "sugar free," but that fail to do so or otherwise fail to comply with the regulation, 21 CFR 101.60(c). Therefore, we are taking this opportunity to remind food manufacturers and distributors of conventional food products that the definition of "sugar free" includes several requirements.

Under the authority of the Nutrition Labeling and Education Act of 1990, FDA issued regulations for the nutrient content claim "sugar free" 58 Federal Register (FR) 2302 at 2415. "Sugar free" is defined in Title 21 of the Code of Federal Regulations 101.60(c) (21 CFR 101.60(c)) as a claim that may be used on a food that contains less than 0.5 g of sugars, as defined in § 101.9(c)(6)(ii), per reference amount customarily consumed and per labeled serving (21 CFR 101.60 (c)). For a food that meets the definition of a "meal" in 21 CFR 101.13(l) or "main dish" in 21 CFR 101.13(m), the food must contain less than 0.5 g of sugars per labeled serving. In addition, such foods may not contain any ingredient that is a sugar or that is generally understood by consumers to contain sugars, unless the listing of the ingredient in the ingredient statement is followed by an asterisk that refers to the statement that appears below the list of ingredients, and that provides: "adds a trivial amount of sugar," "adds a negligible amount of sugar," or "adds a dietarily insignificant amount of sugar."

FDA has historically taken the position that consumers may associate claims regarding the absence of sugar with weight control and with foods that are low calorie or that have been altered to reduce calories significantly. Therefore, the definition for "sugar free" includes the requirement that any food that is not low or reduced in calorie disclose that fact. Without such information some consumers might think the food was offered for weight control. See 56 FR 60421 at 60435. Consequently, the definition for "sugar free" includes the requirement that the food be labeled with the claim "low calorie" or

Figure 2 continued

"reduced calorie" or bear a relative claim of special dietary usefulness labeled in compliance with 21 CFR 101.60(b)(2), (b)(3), (b)(4), or (b)(5) or such claim is immediately accompanied, each time it is used, by one of the following disclaimer statements: "not a reduced calorie food," "not a low calorie food," or "not for weight control" (see 21 CFR 101.60(c)(1)(iii)). The disclaimer statement, when required, must accompany the claim each time it is used. In addition, the disclaimer statement is subject to the requirements of 21 CFR 101.2(c) and must appear prominently and conspicuously but in no case may the letters be less than one-sixteenth inch in height.

FDA encourages food manufacturers and distributors to review their labels and ensure that any food that bears a claim regarding the absence of sugar meet each of the requirements for that claim including the placement and conspicuousness of the disclaimer statement in 21 CFR 101.60(c)(1)(iii) when required. FDA will take appropriate action, consistent with our priorities and resources, when we find problems with the use of nutrient content claims regarding the absence of sugar in foods.

Sincerely,

Barbara O. Schneeman, Ph.D.
Director,
Office of Nutritional Products, Labeling, and Dietary Supplements
Center for Food Safety and Applied Nutrition
Food and Drug Administration

CHAPTER II

METHODOLOGY

The hedonic regression approach has been extensively used in economics and, more specifically, it has been implemented in situations relating to labeling claims. In this approach, a product's price is modeled as a function of its characteristics (Abere 2010). The hedonic regression dates back to 1928 where Waugh (1928) observed wide variation in the prices of asparagus, tomatoes, and hot-house cucumbers. He then analyzed the relationship between prices of these vegetables and the physical characteristics of the products. However, the term "hedonic pricing method" is typically known to come from Court (1939). Court analyzed the relationship between automobile prices and several technical characteristics of the car. Since this time it has seen a wide range of applications throughout the economics literature, including studies utilizing this methodology to examine food labeling claims.

These studies have investigated the effect food product attributes and food labeling statements have on product prices. This methodology enables one to estimate the implicit values that are associated with food product attributes by the use of data on explicit product prices and characteristics (Muth et al 2013). For example, Muth et al. (2013) conducted a study to estimate the value of food labeling statements about health benefits associated with the consumption of certain products. Specifically, using hedonic methods, they estimated a semi-log price regression for breakfast bar and cereal products utilizing Nielsen Scantrack scanner data. They found that several health-focused labeling statements for these products were associated with higher prices, and in particular the "no sugar added" label was estimated to increase the product price by 45.7% for granola and yogurt bars, 27.6% for ready-to-eat cereals, and 20.1% for granola or natural cereals. Another hedonic analysis done by Maguire et al (2004) showed that including an organic label on baby food led to an increase in the amount that consumers were willing to pay for the product. This amounted to a 16-27% increase, or 3¢-4¢ per ounce more, in what consumers paid as a premium. Li and Hooker (2009) used hedonic methods to investigate the use of safety messages on food and beverage product labels. They found evidence that a "preservative free" claim on the label added an average of 5¢ per ounce to yogurts as well as a price premium for an "E. coli free" attribute.

Another example of a hedonic price analysis was a study by Steiner (2004) estimating implicit prices for labeling attributes of Australian wines in the British wine market. A different study using hedonic pricing methodology applied to wine was conducted by Combris, Lococq, and Visser (1997). They studied the objective characteristics of Bordeaux wine as well as the price quality relationship. They found that the market price of Bordeaux wine is primarily impacted by the characteristics appearing on the label of the bottle.

Anstine (2007) examined consumers' willingness to pay for milk and yogurt labeled as "all natural". He found that this "all natural" claim was associated with a 40% (or about 34¢ per ounce) price premium for the attribute in yogurt. Satimanon and Weatherspoon (2010) used hedonic price analysis to study price premiums for sustainable attributes of fresh eggs. They found eggs that were labeled as welfaremanaged had a price premium of 3.57¢ per egg. Additionally, Xiao (2012) used the hedonic methodology to examine price differences due to characteristics of retail oatmeal and milk.

Importantly, several studies from the academic literature have dealt with the determination of consumers' willingness to pay ("WTP") for functional foods. Health attributes can be interpreted as a characteristic of any food. Moro, Sckokai, and Veneziani (2012) conducted a stated-choice experiment in June 2011 on a sample of 600 Italian consumers in order to elicit the WTP for yogurt enriched with catechines (natural phenolic compounds that are a source of antioxidants). These researchers also found that the estimated average WTP was 40%. That is, this sample of Italian consumers was willing to pay on average a 40% price premium for yogurt enriched with catechines.

Hirogaki (2013) surveyed the preferences of 270 students of economics in Hiroshima in April/May 2012 to determine their WTP for foods labeled with specified health uses. He also found that this sample of Japanese consumers were willing to pay on average a 20% price premium for foods labeled with specified health uses.

Miskolci (2011) analyzed selected studies pertaining to WTP on the part of consumers in the Czech Republic for improvements in food quality, guaranteed food quality, and for functional food. Consumers from the Czech Republic were willing to pay on average an 11.2% premium for food quality improvement, a 12.3% to 15.4% premium for guaranteed food quality, and a 15.6% premium for functional foods.

Markosyan, Wahl, and McClusky (2007) measured consumers' response to apples with "naturally enriched antioxidant coatings" based on surveys conducted in grocery stores in Seattle, Washington and in Spokane, Washington. It was estimated that consumers, on average, were willing to pay a four percent to eight percent premium for apples with "naturally enriched antioxidant coatings."

Finally, Mayen (2013), using conjoint analysis based on surveys of the U.S. population, found that labeling packages of tree nuts (almonds, pecans, walnuts, and pistachios) with the language "High in Antioxidants" positively influenced consumer preferences.

Model Development

The methodology utilized in this analysis corresponds to a revealed preference approach as the actual prices paid for the product are employed in the analysis instead of the expressed willingness to pay as determined by experiments or surveys. These aforementioned studies reinforce the fact that the use of hedonic regression is widely regarded in economic literature as an acceptable method for quantifying the effect of product attributes, such as labeling claims, on product prices.

With the use of hedonic regression analysis, the basic idea is that a food or beverage product is comprised of a series of attributes. The bundle of all of the attributes defines the unit price, which will imply that the product prices are capable of being decomposed into implicit prices for each individual attribute. These implicit prices are referred to as hedonic prices, and intrinsic values of these many different attributes are able to be recovered by specifying the prices of the food or beverage product as a function of these attributes. With the hedonic regression approach, one can identify what level of impact the labeling claim had on the prices of the products in question.

In applying the hedonic regression model to the hypothetical case, the following hypotheses were statistically tested:

$$H_0: \beta_{LC} = 0$$

$$H_A: \beta_{LC} > 0$$

Null hypothesis: The inclusion of the labeling statement “No Sugar Added” has no statistical impact on prices paid by consumers of Brand 1 juice products.

Alternative hypothesis: The inclusion of the labeling statement “No Sugar Added” is positively related to the prices paid by consumers of Brand 1 juice products.

In the use of the hedonic model, a semi-log regression was specified of prices of Brand 1’s cranberry juice products as well as of other comparator products as follows:

$$\ln(P) = f(LC, PA, OF)$$

where LC is a binary variable dealing with the Labeling Claim in question (in the case of Brand 1, “No Sugar Added”), PA is a vector of other product attributes (Package Size, Brand, Package Type, Flavor, Diet, Light, Low Calorie, and Juice vs. Juice Cocktail), and OF corresponds to other factors to control for in the regression (year, seasonality, volume sold). Since this model is using a semi-log regression and the presence of the label statement is a binary variable, the coefficient of this variable corresponds to the implicit value of the labeling statement in percentage terms. Simply speaking, this coefficient corresponds to the percentage change in the price of the product as a result of the labeling claim, controlling for all other influencing factors. The actual percentage change as a result of the coefficient can be recovered utilizing the following formula:

$$(e^{(\beta_i)} - 1) \times 100,$$

where β_i is the estimated coefficient for each binary variable in question.

Once this coefficient has been estimated, the subsequent step is to assess damages associated with the labeling claim. If records were available of the Defendant's sales to wholesalers and retailers during the time period of the class action, then this percentage change in price could be multiplied by the amount of total sales to obtain the extent of disgorgement or damages. Another method of calculating damages revolves around the utilization of recorded retail sales from a third-party vendor like Nielsen or Information Resources, Inc. (IRI). Given the absence of any records from the Defendant, we accessed recorded retail sales available from Nielsen over the entire United States for the period 2006 to 2011. With this method, the initial step is to calculate the sum of retail sales of Brand 1 cranberry juice products possessing the labeling claim over the class period; the subsequent step involves the product of the percentage change coefficient to obtain a measure of disgorgement or damages. If there were no markup from the manufacturer to the retailer, this amount would be the damages due the class.

However, in actual business practice, there is a markup that will occur between the manufacturer and the consumer. Hottman (2014) analyzed consumer demand and oligopolistic retail competition in order to study mechanisms in which retailers' impact allocative efficiency and consumer welfare. In so doing, he estimated a monopolistically competitive markup for retail products to be approximately 28%. Another analysis by Feenstra and Shapiro (2003) estimated the "preferred" markup ratio for bottled juice to be approximately 30%, and frozen juice to be approximately 25%. This study then estimated retail markup ratios in which it placed the markup for bottled juice at approximately 20%. Based on these examples, this analysis sets an assumed range of markup to be 20% to 30%. Taking into account this range of markup, a range of the measure of disgorgement or damages is obtained.

Data Analysis

Nielsen Scantrack Data

The data used in this thesis involved retail scanner data from Nielsen Company's Scantrack store scanner data made available through the Kilts Center for Marketing at the University of Chicago's Booth School of Business. These data are based on a nation-wide sample of point of sale information from more than 35,000 participating retail outlets across the country over the time period of 2006 to 2011. This analysis incorporated nationwide sales; the reasoning behind this is that Brand 1 sells its products over the entire United States and not just in any particular state. The dataset utilized in this thesis were only available over the period 2006 to 2011. Ideally, in order to address the complaint, data corresponding to the relevant class period would be used and in the hypothetical example only data pertinent to the regional retail outlets.

Weekly sales data for 2.6 million individual Universal Product Codes (UPCs) were available from this third party vendor. In the dataset, each UPC contains text information about the product characteristics as well as brand, multi-packaging, size, packaging type, and other product characteristics. The product category for this analysis was defined as ready-to-drink shelf stable juices, focusing on the flavor cranberry.

From this dataset, weekly sales data from the available time period and product category were pooled for four brands: Brand 1, Brand 2, Brand 3, and Brand 4. Brand names are not disclosed to preserve anonymity and confidentiality. This pooling resulted in 65,689 available weekly observations; essentially, there were 312 weekly time-series observations, but due to the many different UPCs associated with the brands the number of available observations reached 65,689.

In order to make this process manageable, the focus was on maintaining a representative sample of the data, while at the same time reducing the overall number of observations with which to work. Brand 1 accounted for a total of 24,258 weekly observations. Observations of less than $10,000 in weekly sales associated with the Brand 1 brand were dropped; this reduced the number of Brand 1 weekly observations by 14,044 while only removing 5.8% of the total sales volume of this brand. Brand 2 accounted for a total of 39,423 weekly observations. Observations of less than $2,000 in weekly sales associated with Brand 2 were dropped; this filtering reduced the number of Brand 2 observations by 24,953 while only removing 7.5% of the total sales volume of the respective Brand 2. Brand 3 accounted for a total of 1,015 weekly observations. Observations of less than $500 in weekly sales associated with the Brand 3 brand were dropped; this filtering reduced the number of Brand 3 brand weekly observations by 668 while only removing 14.0% of the total sales volume of this brand. Brand 4 accounted for a total of 993 weekly observations. Observations of less than $1,500 in weekly sales associated with this brand were dropped; this filtering reduced the number of Brand 4 brand by 314 while only removing 5.8% of the total sales volume of this brand.

Dropping these observations increased manageability through the removal of 39,979 observations from the dataset, while still maintaining representativeness by keeping 93.8% of the total sales of the period. Additionally, this process maintained representativeness of each brand by keeping 94.2% of Brand 1 sales, 92.5% of Brand 2 sales, 86.1% of Brand 3 sales, and 94.2% of Brand 4 sales. The total number of observations used in the analysis was 25,710. But due to additional variable screens described later, the number of observations on which this analysis is based was 24,578. The majority of the observations are associated with Brand 1's as well as with Brand 2's products. As exhibited in Table 1, Brand 1 had the largest sales of the brands over the time period, followed by Brand 2, Brand 4, and Brand 3, respectively. Brand 1 had the highest market share at approximately 75%, even though this brand accounted for only 38% of the observations.

Table 1: Total Sales Organized by Brand

Brand	Sum	Obs.	Market Share
Brand 1	$ 521,363,985	9,362	75.6%
Brand 2	$ 163,080,652	14,215	23.7%
Brand 3	$ 853,237	322	0.1%
Brand 4	$ 4,046,962	679	0.6%
All	$ 689,344,836	24,578	100.0%

Dependent or Endogenous Variable

The dependent or endogenous variable for the hedonic regression is price per ounce. As this metric was not an observed variable available in the dataset, the variable was calculated as a ratio for each observation from two available variables: total sales and ounces sold. Price per ounce was calculated as:

$$Price\ per\ Ounce = \frac{Total\ Sales}{Ounces\ Sold}$$

Differences in retail prices may exist across different retail outlets and/or different geographical markets in any given time period. As well, promotions may exist in any given time period. To that end, a weighted average price was generated for the cranberry juice products at issue for each UPC over the time period 2006 to 2011. The weights used in this calculation are the number of units sold of the specific UPC across the United States in any given week over the 2006 to 2011 period. Consequently, this weighted average price constitutes the representative price in any given period for any given UPC. Importantly, this weighted average price is common to the class of purchasers. Because any price differences attributed to region, distribution channels, and promotion are part of the dependent variable in the respective hedonic model, there is no need to consider these as explanatory variables.

Table 2: Descriptive Statistics of Price Per Ounce (in $/oz)

Brand	Mean	Median	Max	Min.	Std. Dev.	Obs.
Brand 1	0.04352	0.04234	0.07722	0.01912	0.00926	9362
Brand 2	0.03810	0.03566	0.16889	0.00895	0.01481	14215
Brand 3	0.08587	0.10137	0.12297	0.02478	0.03206	322
Brand 4	0.03146	0.03242	0.04055	0.01664	0.00408	679
All	0.04060	0.03748	0.16889	0.00895	0.01447	24578

From Table 2, the average price per ounce was roughly $0.04. Brand 3 had the highest average price at nearly $0.09 per ounce, ranging from $0.02 per ounce to $0.12 per ounce. On average, Brand 1 was slightly more than $0.04 per ounce, ranging from nearly $0.02 per ounce to $0.08 per ounce. The average price of Brand 2 was just under $0.04 per ounce, varying from $0.01 per ounce to $0.17 per ounce. Finally, Brand 4 had the lowest average price at slightly more than $0.03 per ounce, ranging from slightly less than $0.02 per ounce to $0.04 per ounce.

Explanatory Variables

Labeling Claim

Labeling claim is a binary variable that was assigned a value of 1 if the misleading labeling claim in question ("No Sugar Added") was present and 0 if otherwise. Two of the brands in this hypothetical case, namely Brand 1 and Brand 3 had the misleading claim present on their label, "No Sugar Added." For the purpose of the analysis in this thesis, Brand 2 and Brand 4 did not have the claim associated with its label; as such, the value of the labeling claim variable was zero. From Table 3, out of the 24,578 observations, 9,684 or close to 40% had the labeling claim of "No Sugar Added."

Table 3: Labeling Claim Variable

Labeling Claim	Count	Percent	Cumulative Count	Cumulative Percent
No	14894	61%	14894	60.60%
Yes	9684	39%	24578	100.00%
Total	24578	100%	24578	100.00%

Container Size

It was expected that container size would vary inversely with price. Essentially, this explanatory variable allows for economies of scale, and one would expect larger containers to be associated with a lower price per ounce than for smaller containers, all other factors invariant. This metric was not an observed variable available in the dataset either, and so it was calculated utilizing two other variables from the dataset: units sold and ounces sold. Container size was calculated as:

$$Container\ Size = \frac{Ounces\ Sold}{Units\ Sold}$$

Using this metric, a total of 14 different package sizes were evident in the dataset ranging from 14 oz to 240 oz. However, an issue developed with the container size variable and the multipack variable to be discussed later. All of the observations for 60 oz and 240 oz containers were precisely the same observations for the multipack variables of 6 and 24 packs; consequently, this situation corresponded to perfect multicollinearity between these variables. For this reason, 338 observations were then dropped to avoid perfect collinearity. For the remaining twelve container sizes, separate binary variables were created to be included in the analysis, one for each size.

As exhibited in Table 4, the most common container size by far was 64 oz which accounted for almost 70% of observations. The next largest number of observations belonged to 192 oz, 48 oz, and 128 oz container sizes respectively. These three container sizes accounted for roughly 20% of the observations.

Table 4: Container Size Variable

Container Sizes (OZ)	Count	Percent	Cumulative Count	Cumulative Percent
14	179	0.73%	179	0.73%
16	114	0.46%	293	1.19%
32	341	1.39%	634	2.58%
33.8	113	0.46%	747	3.04%
46	489	1.99%	1236	5.03%
48	1710	6.96%	2946	11.99%
64	16936	68.91%	19882	80.89%
96	191	0.78%	20073	81.67%
101	313	1.27%	20386	82.94%
101.4	883	3.59%	21269	86.54%
128	1019	4.15%	22288	90.68%
192	2290	9.32%	24578	100.00%
Total	24578	100%	24578	100.00%

Brand

Four brands were selected to be included in this analysis: Brand 1, Brand 2, Brand 3, and Brand 4. At the very core of this thesis is the notion that consumers are willing to pay different prices for comparable products due to product differentiation, and brand is one of the primary ways that manufacturers differentiate their product. Each brand was created as a separate dummy variable in order to measure the effect of brand on prices.

As shown in Table 5, Brand 2 accounts for the largest share of the observations, with almost 58% of the total observations, followed by Brand 1 with 38%; Brand 4 and Brand 3 brands make up only a combined 4% of the total number of observations.

Table 5: Brand Variables

Brand	Count	Percent	Cumulative Count	Cumulative Percent
Brand 1	9362	38.09%	9684	39.40%
Brand 2	14215	57.84%	23899	97.24%
Brand 3	322	1.31%	322	1.31%
Brand 4	679	2.76%	24578	100.00%
Total	24578	100%	24578	100.00%

Flavor

The flavor variable was developed from the text description associated with the UPC. Originally, a total of 25 different flavors/flavor combinations were contained in the dataset. However, throughout the data cleaning process, specifically in making the decisions to drop observations based on sales, many of these flavors were no longer part of the dataset. Since the analysis is based on comparable products of Brand 1's cranberry juice, only flavors which were related to cranberry in some fashion were included in the analysis (e.g. cranberry/apple blend, cranberry/lime blend, and white cranberry). A total of 13 different binary flavor variables were considered in the analysis (see Table 6), with the most common variables being CBY, CBY/RP, CBY/GRP, CBY/APL, and CBY/POM.

Table 6: Flavor Variables

Flavor	Count	Percent	Cumulative Count	Cumulative Percent
CBY	8378	34.09%	8378	34.09%
CBY/GRP	3935	16.01%	12313	50.10%
CBY/POM	1390	5.66%	13703	55.75%
CBY/RP	4296	17.48%	17999	73.23%
WH CBY/PCH	817	3.32%	18816	76.56%
CBY/BB	780	3.17%	19596	79.73%
CBY/LM	176	0.72%	19772	80.45%
CBY/APL	2717	11.05%	22489	91.50%
CBY/STRBY	469	1.91%	22958	93.41%
CBY/TAN	167	0.68%	23125	94.09%
WH CBY	588	2.39%	23713	96.48%
WH CBY/STRBY	597	2.43%	24310	98.91%
WH CBY/STRBY/GP	268	1.09%	24578	100.00%
Total	24578	100%	24578	100.00%

The flavor variables are given in this shorthand format in the UPC description. The lexicon of these thirteen flavor variables is shown in Table 7.

Table 7: Flavor Variable Definition

UPC Description	Flavor
CBY	Cranberry
CBY/GRP	Cranberry Grape
CBY/POM	Cranberry Pomegranate
CBY/RP	Cranberry Raspberry
WH CBY/PCH	White Cranberry Peach
CBY/BB	Cranberry Blueberry Blackberry
CBY/LM	Cranberry Lime
CBY/APL	Cranberry Apple
CBY/STRBY	Cranberry Strawberry
CBY/TAN	Cranberry Tangerine
WH CBY	White Cranberry
WH CBY/STRBY	White Cranberry Strawberry
WH CBY/STRBY/GP	White Cranberry Strawberry Grape

Package Type

Further, the package type variable was developed from the text description of the UPC, and two resulting container types of either glass or plastic were identified. At this time, an additional 186 observations were dropped due to having an inconsistent/unidentifiable container type listed in the text description. Again, as this number was small relative to the overall sample size, dropping these observations was not considered a problem. Binary variables then were created for these container types. It was expected that if the product was placed in a glass container relative to other containers, it would command a higher price per ounce. The rationale for this hypothesis is attributed to the increased cost of materials expected to be associated with a glass container; alternatively, consumers may be willing to pay a premium for the glass containers for perceived superior quality of the product.

Table 8: Package Type Variables

Container Type	Count	Percent	Cumulative Count	Cumulative Percent
Unspecified	662	2.69%	662	2.69%
Plastic	21926	89.21%	22588	91.90%
Glass	1990	8.10%	24578	100.00%
Total	24578	100%	24578	100.00%

As exhibited in Table 5, the most common package type was plastic containers. Over 90% of the sample of observations was of the plastic container type.

Multi Pack

The multi pack variable, identifying if the product was sold as a group of containers, also was developed by utilizing the text description of the UPC. Originally, two different combinations of multi packs were identified, namely a single (no multipack), 2 multi pack, 4 multi pack, 6 multi pack, and 24 multi pack. However, as mentioned previously, all of the observations for the 6 and 24 multi pack observations were exactly the same observations for the container size variables of 60 oz and 240 oz. To alleviate the perfect multicollinearity between the variables, the 6 pack and the 24 pack variables were dropped from the analysis.

Table 9: Multi Pack Variables

Multipack	Count	Percent	Cumulative Count	Cumulative Percent
Single	21804	88.71%	21804	88.71%
2 Pack	2013	8.19%	23817	96.90%
4 Pack	761	3.10%	24578	100.00%
Total	24578	100%	24578	100.00%

As exhibited in Table 9, the single (no multipack) occurred nearly 90% of the time in the sample.

Other Health Characteristic Variables

In the text description of the UPC, other product characteristics were identified and created as different binary variables for attributes that could potentially affect the price of the product. These product characteristics were light, low calorie, and diet. The reasoning for identifying these in the analysis is that some consumers might be willing to place a price premium on the health benefits associated with these product attributes apart from the labeling claim "No Sugar Added." As shown in Table 10, roughly 17% of the observations were associated with the terms "light", "low calorie", and "diet." The most common of these was the characteristic "light."

Table 10: Other Health Characteristics Variables

Other Health Characteristics	Count	Percent
Light	2780	11.31%
Low Calorie	807	3.28%
Diet	701	2.85%

Volume

The explanatory variable volume is a proxy for a set of economic factors which may affect price, notably income, advertising, prices of substitute products, and prices of complementary products. As exemplified in any textbook in microeconomics, these factors affect the demand for any product. As changes in volume (quantity sold) of any good are affected due to changes in these aforementioned factors, subsequently changes in prices are affected as well. In fact, the expectation is for changes in volume and changes in prices to be inversely related.

To illustrate, if any manufacturer’s advertising expenditures increased, it is likely that quantity sold would increase, all other factors invariant. If volume or quantity sold increased, then prices of products would likely decrease, controlling for all other factors. Product characteristics may or may not be influenced by advertising, but the value of these attributes is already measured in the hedonic regression (Rosen, 1974). Moreover, because of the presence of the variable volume (quantity sold) in the hedonic model, we control for potential impacts of changes in income, changes in the prices of substitute products, and changes in the price of complementary products. This framework is consistent with the work of Nerlove (1995).

Volume as a variable is the quantity sold in ounces of the product for each observation. As exhibited by Table 11, Brand 1 had the largest ounces sold over Brand 3 Brand 4 as well as over Brand 2.

Table 11: Volume (ounces sold)

BRAND	Mean	Median	Max	Min.	Std. Dev.	Obs.
Brand 1	1418905.0	622272.0	31966464.0	131088.0	2352599.0	9362
Brand 2	329491.6	175616.0	4975040.0	12224.0	447241.8	14215
Brand 3	52783.9	12740.0	944256.0	4760.0	110460.4	322
Brand 4	212025.1	146752.0	1954176.0	42688.0	216071.1	679
All	737589.4	302387.4	31966464.0	4760.0	1584975.0	24578

Seasonality

The prices of cranberry juice may vary during the year. To capture this potential effect, seasonality was incorporated into the analysis through the use of monthly dummy variables. As exhibited in Table 12, the number of observations is nearly uniformly distributed throughout the year.

Table 12: Seasonality Variables

Month	Count	Percent	Cumulative Count	Cumulative Percent
Jan	2261	9.20%	2261	9.20%
Feb	2020	8.22%	4281	17.42%
Mar	2142	8.72%	6423	26.13%
Apr	2048	8.33%	8471	34.47%
May	2130	8.67%	10601	43.13%
Jun	1914	7.79%	12515	50.92%
Jul	2018	8.21%	14533	59.13%
Aug	2020	8.22%	16553	67.35%
Sep	1958	7.97%	18511	75.32%
Oct	2026	8.24%	20537	83.56%
Nov	1927	7.84%	22464	91.40%
Dec	2114	8.60%	24578	100.00%
Total	24578	100%	24578	100.00%

Year

As exhibited in Table 13, the number of observations is nearly uniformly distributed throughout the sample period from 2006 to 2011. Binary variables were used to account for these variables. Again, the number of observations is nearly uniformly distributed over the 2006 to 2011 period.

Table 13: Year Variables

Year	Count	Percent	Cumulative Count	Cumulative Percent
2006	4122	16.77%	4122	16.77%
2007	4335	17.64%	8457	34.41%
2008	4212	17.14%	12669	51.55%
2009	4322	17.58%	16991	69.13%
2010	3833	15.60%	20824	84.73%
2011	3754	15.27%	24578	100.00%
Total	24578	100%	24578	100.00%

Juice VS Juice Cocktail

Two other product characteristics identifying if the product were marked as juice or juice cocktail were observed in the text description of the UPC. In order to account for the effect of these product attributes on prices, they were each included in the hedonic analysis as binary variables. One might expect that a product identified as juice as opposed to a juice cocktail would have a positive effect on price because of perceived quality differences between the two in the eyes of the consumer. As exhibited in Table 14, nearly half of the observations in the sample were for the trait “juice cocktail”, and roughly 20% were for the trait “juice.” For the remaining observations, no specification of either “juice” or “juice cocktail” was possible given the text description associated with the UPC.

Table 14: Juice and Juice Cocktail Variables

Juice vs Juice Cocktail	Count	Percent	Cumulative Count	Cumulative Percent
Unspecified	7844	31.91%	7844	31.91%
Juice	4747	19.31%	12591	51.23%
Juice Cocktail	11987	48.77%	24578	100.00%
Total	24578	100%	24578	100.00%

Final Stages of Model Development

A data issue emerged with including both brand and labeling claim as explanatory variables in the analysis. Specifically, a near perfect multicollinearity situation among the binary variables which comprise brand (Brand 1, Brand 2, Brand 3, and Brand 4) and labeling claim (two, “No Sugar Added” label present or not) in the dataset. Near perfect multicollinearity exists when two or more of the explanatory variables in the analysis possess a high degree of correlation. While collinearity issues do not affect the R^2 or goodness-of-fit statistic, these issues impact the signs and magnitudes of the estimated coefficients of the correlated explanatory variables as well as the variances and standard errors of the estimated coefficients. Higher variance and standard errors would imply that the t-statistics for the coefficients are lower than they might actually be, increasing the possibility of a type II error. Consequently, this situation may lead to the conclusion that explanatory variables are not statistically significant (their coefficients are not statistically different from zero) when they in fact may be.

There are options to consider when encountering such a problem. A popular option for overcoming near perfect multicollinearity is to drop one of the highly correlated explanatory variables. Since the objective is to understand the relationship between the labeling claim and the price, it was decided to drop the brand variable. A down side of this option is that it could potentially lead to omitted variable bias. This situation is not an issue with the methodology, in this case the use of hedonic price analysis. Instead, it is a data issue. Potential steps to take in the future to mitigate this issue are discussed in the conclusion section.

During the data cleaning process, the focus was on maintaining a representative sample, while increasing manageability. This process allowed the dataset to be reduced by a large number of observations while still maintaining approximately 94% of total sales volume. Once the data had been cleaned and all observations had been put through various filtering processes, the resulting data were then compiled and stacked into one clean dataset. The final dataset employed in the hedonic regression included 24,578 stacked observations, with 51 variables, including the dependent variable. With the very large number of observations included in the dataset, no issues are evident with degrees of freedom, even with the notable number of explanatory variables.

When using linear regression, the method maintains a certain level of flexibility in describing the data, flexibility that derives from the ability to modify variables with functions of the variables in the dataset. Two variables in this analysis, volume and price per ounce, are transformed using the natural log transformation.

With this backdrop, the model specification employed in the hedonic regression analysis is as follows:

$$
\begin{aligned}
\ln(price\ OZ) = {} & \beta_0 + \beta_1 \ln(oz_{sold}) + \beta_2 DT + \beta_3 LC + \beta_4 LT + \beta_5 Label\ Claim \\
& + \beta_6 JAN + \beta_7 FEB + \beta_8 MAR + \beta_9 APR + \beta_{10} MAY + \beta_{11} JUN + \beta_{12} JUL \\
& + \beta_{13} AUG + \beta_{14} SEP + \beta_{15} OCT + \beta_{16} NOV + \beta_{17} YEAR_{2006} \\
& + \beta_{18} YEAR_{2007} + \beta_{19} YEAR_{2008} + \beta_{20} YEAR_{2009} + \beta_{21} YEAR_{2010} \\
& + \beta_{22} FLAV_{CBYGRP} + \beta_{23} FLAV_{CBYPOM} + \beta_{24} FLAV_{CBYRP} \\
& + \beta_{25} FLAV_{WHCBYPCH} + \beta_{26} FLAV_{CBYBB} + \beta_{27} FLAV_{CBYLM} \\
& + \beta_{28} FLAV_{CBYAPL} + \beta_{29} FLAV_{CBYSTRBY} + \beta_{30} FLAV_{CBYTAN} \\
& + \beta_{31} FLAV_{WHCBY} + \beta_{32} FLAV_{WHYCBYSTRBY} + \beta_{33} FLAV_{WHCBYSTRBYGP} \\
& + \beta_{34} CONT_{PL} + \beta_{35} CONT_{GL} + \beta_{36} CONTSIZE_{14} + \beta_{37} CONTSIZE_{16} \\
& + \beta_{38} CONTSIZE_{32} + \beta_{39} CONTSIZE_{33.8} + \beta_{40} CONTSIZE_{46} \\
& + \beta_{41} CONTSIZE_{48} + \beta_{42} CONTSIZE_{96} + \beta_{43} CONTSIZE_{101} \\
& + \beta_{44} CONTSIZE_{101.4} + \beta_{45} CONTSIZE_{128} + \beta_{46} CONTSIZE_{192} \\
& + \beta_{47} MULTIPACK_2 + \beta_{48} MULTIPACK_4 + \beta_{49} JC + \beta_{50} JCCKL + \varepsilon
\end{aligned}
$$

Variables corresponding to individual UPCs constructed for the hedonic regression analysis are: (1) price-the dependent variable for the hedonic regression in dollars/ounce for each UPC in logarithmic form (constructed by dividing dollar sales by volume sales); (2) variables pertaining to health characteristics (DT, LC, and LT); (3) container size-in reference to product weight per container. Package size or container size has been shown in the economic literature to impact prices of various food and beverage products; (4) seasonality-a set of monthly dummy variables designed to capture effects on prices month-to-month within a year. The reference month for seasonality is December. This designation is arbitrary and does not affect the econometric results; (5) volume--this explanatory variable is a proxy for a set of economic factors which may affect price, notably income, advertising, prices of substitutes, and prices of complements; (6) the variable labeling claim corresponds to a dummy variable, 1 if the claim "No Sugar Added" appear on the label and 0 if not. The reference category is that the labeling claim does not appear on the label; (7) product characteristics-various dummy variables are constructed to capture qualitatively the impact of product characteristics on prices (e.g., flavor, type of container (plastic, glass or not specified), juice or juice cocktail, and multipack); and (8) a set of year dummy variables. The reference year is 2011. This designation is arbitrary and does not affect the econometric results.

Note that the dependent variable and the volume variable (ounces sold) are in logarithmic form. As such, the estimated coefficient associated with the logarithm of the volume variable is the price flexibility, the percentage change is price attributed to a one percent change in quantity sold. Because the presence or absence of the labeling statement is a binary (dummy variable), the coefficient associated with this variable can be interpreted with a proper transformation as the percentage change in the price of the product attributed to the labeling claims while controlling for all of the factors previously. This model specification is not only consistent with the extant literature (see

Muth et al 2013) but also consistent with Rubinfeld's (2000) reference guide on multiple regression. Rubinfeld (p. 181) states that "multiple regression may be useful in measuring the magnitude of a particular effect."

CHAPTER III

EMPIRICAL RESULTS

In this chapter, the empirical results associated with the hedonic regression analysis for product characteristics on ready-to-drink shelf stable cranberry juice are reported. In the hedonic price regression, the data correspond to stacked time-series and cross-sectional observations. Given the unbalanced nature of the stacked data (unequal number of time-series observations across the UPCs), the hedonic model was estimated using ordinary least squares (OLS). To account for the presence of both heteroscedasticity and autocorrelation of unknown form, the Newey-West HAC procedure (1987) is implemented to adjust the standard errors associated with the estimated parameters. The acronym HAC relates to the words heteroscedasticity, autocorrelation, and consistent. With the Newey-West procedure, the estimated coefficients are exactly the same as those estimated by OLS.

The results for this analysis were derived using the EVIEWS statistical software (version 8.0), and are presented in Table 15. In this table, the parameter estimates, standard errors, t-statistics, and p-values associated with the respective coefficients of the many variables listed in the data section of this thesis are presented. In interpreting the results, it should be noted that the majority of the estimated coefficients in the hedonic regression model are statistically significant. The level of significance chosen for this analysis is 0.05. So, any p-value associated with the estimated coefficients that is less than 0.05 is deemed to be statistically different from zero. The goodness-of-fit for the model, or the R^2 statistic, is 0.7533, and so it can be interpreted that this semi-log hedonic regression model explains over 75% of the variation in price of the products.

The statistically significant drivers of prices of shelf stable cranberry juices are: (1) volume; (2) the “low calorie” claim; (3) the “No Sugar Added” claim; (4) year; (5) flavor; (6) container size; (7) multipack; and (8) juice or juice cocktail. The set of estimated coefficients associated with seasonality is not statistically significant as a group. Hence, seasonality is not a driver of prices of shelf stable cranberry juices. The “diet” and “light” claims also are not significant drivers of prices of shelf stable cranberry juices. Finally, the type of container (plastic or glass) has no perceptible influence of the prices of shelf stable cranberry juices.

Prices are lower by 5.6% with the “low calorie” claim than without this claim. Prices are lower in 2006 and 2007 by 5.7% and 2.9% respectively relative to 2011, but prices are higher in 2008 and 2009 by 3.3% and 3.5% relative to 2011.

Relative to prices of just the cranberry flavor, prices of all other variations of the cranberry flavor are significantly lower. The base flavor for the category was cranberry, and all of the mixed flavors tended to have a negative impact on prices relative to the regular cranberry flavor. These negative impacts ranged from lowering the price per ounce by 3.4% with white cranberry peach flavor to lowering the price by 17.1% with cranberry lime flavor.

Speculative reasons as to why all of the mixed flavor variations lowered price per ounce can fall under two categories: cost-based pricing and demand-based pricing. It could potentially be that the inputs needed for the regular cranberry flavor are the most expensive relative to other flavors, and by blending this more expensive juice with less expensive juices, manufacturers are lowering their cost per ounce to produce the product. Another potential explanation is that the prices seen on the shelf are determined more by demand-based factors. Retailers will calculate elasticities of the products and set prices to a profit maximizing level based on consumers' willingness to pay as opposed to the costs of production of the product. The reason that the regular cranberry flavor costs more per ounce than the mixed flavors could be that the demand for that flavor is much higher than the other flavors and retailers are attempting to capitalize on that demand. This finding is supported by the fact that in the dataset, sales of the regular cranberry flavor account for approximately 53% of the total value of the category sales, meaning that it is by far the most popular flavor.

As expected, container sizes less than 64 ounces have higher prices in relation to the base or reference category container size of 64 ounces. That is, a premium is to be paid for smaller container sizes compared to the standard container size of 64 ounces. The magnitude and signs of the coefficients adhere to our initial logical thinking for the most part; the estimated coefficients of largest container sizes (128 ounces and 192 ounces) have a negative sign, and so relative to the standard container size of 64 ounces, prices of these container sizes are lower as much as 25%. Simply put, manufacturers capitalize on economies of scale.

Of the multi pack variables, single (no multipack) was the base, so the coefficients of the remaining variables are relative to this category. Both of the remaining multipack variables are statistically significant, with the sign of the 2 pack being negative and the sign of the 4 pack being positive. A negative sign makes logical sense as this finding could partially be explained by the economies of scale argument or because of promotional deals. However, the positive sign on the 4 pack variable is difficult to explain.

For the juice and the juice cocktail attributes, the unspecified category was set as the base. The coefficients of both the juice and juice cocktail variables are significant. However, the magnitude of the juice coefficient is very high, suggesting that price per ounce is higher by 28.4% relative to the price per ounce of the unspecified category. Perhaps this finding is intuitively appealing in that one could expect consumers to be willing to pay a premium for a product that they may identify as being made from pure juice. Consumers may be willing to pay more for this characteristic than for a juice that is processed using other ingredients. Relative to the unspecified category, prices are higher by nearly 5% for the juice cocktail attribute.

The own-price flexibility of shelf stable cranberry juices is estimated to -0.055. The magnitude and sign are on par with the extant literature. Hence as volume sold increases by 10%, all other factors invariant, then prices decrease by 0.55 %.

Table 15: Estimated Coefficients, Standard Errors, t-Statistics, and p-Values of the Semi-Log Hedonic Regression

Dependent Variable: LOG(PRICE_PER_OZ)
Included observations: 24578
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 14.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.672755	0.050600	-52.82169	0.0000
LOG(OZ_SOLD)	-0.055071	0.003607	-15.26813	0.0000
DT	-0.004574	0.017370	-0.263304	0.7923
LC	-0.057684	0.009886	-5.834751	0.0000
LT	0.006105	0.008043	0.759062	0.4478
LABEL_CLAIM	0.225919	0.009466	23.86568	0.0000
JAN	0.010034	0.005566	1.802865	0.0714
FEB	0.004235	0.006582	0.643392	0.5200
MAR	-0.005262	0.007470	-0.704350	0.4812
APR	0.007863	0.007861	1.000224	0.3172
MAY	0.017745	0.007638	2.323279	0.0202
JUN	0.006294	0.007759	0.811187	0.4173
JUL	0.014884	0.007761	1.917736	0.0552
AUG	0.009511	0.008063	1.179517	0.2382
SEP	0.008750	0.007720	1.133430	0.2570
OCT	0.000416	0.006809	0.061096	0.9513
NOV	-0.008638	0.004530	-1.906734	0.0566
YEAR_2006	-0.059133	0.010520	-5.620789	0.0000
YEAR_2007	-0.029816	0.010049	-2.967179	0.0030
YEAR_2008	0.032810	0.010124	3.240659	0.0012
YEAR_2009	0.034641	0.010314	3.358562	0.0008
YEAR_2010	0.002506	0.010061	0.249065	0.8033
FLAV_CBY_GRP	-0.052081	0.007975	-6.530605	0.0000
FLAV_CBY_POM	-0.066931	0.012230	-5.472835	0.0000
FLAV_CBY_RP	-0.066559	0.009063	-7.344281	0.0000
FLAV_WH_CBY_PCH	-0.034120	0.011307	-3.017595	0.0026
FLAV_CBY_BB	-0.102682	0.016115	-6.371885	0.0000
FLAV_CBY_LM	-0.187714	0.055080	-3.408026	0.0007
FLAV_CBY_APL	-0.159113	0.017219	-9.240363	0.0000
FLAV_CBY_STRBY	-0.102310	0.012214	-8.376674	0.0000
FLAV_CBY_TAN	-0.138963	0.012957	-10.72508	0.0000
FLAV_WH_CBY	-0.091394	0.013094	-6.979727	0.0000
FLAV_WH_CBY_STRBY	-0.075587	0.012447	-6.072861	0.0000
FLAV_WH_CBY_STRBY_GP	-0.076385	0.015966	-4.784352	0.0000
CONTAINER_PLASTIC	0.008529	0.009294	0.917711	0.3588
CONTAINER_GLASS	0.039982	0.021544	1.855823	0.0635
CONTAINER_SIZE_14	0.693363	0.029888	23.19890	0.0000
CONTAINER_SIZE_16	0.377670	0.032126	11.75578	0.0000
CONTAINER_SIZE_32	0.762887	0.058176	13.11336	0.0000
CONTAINER_SIZE_33.8	0.021603	0.094899	0.227637	0.8199
CONTAINER_SIZE_46	0.018321	0.013782	1.329343	0.1837
CONTAINER_SIZE_48	0.049276	0.015740	3.130715	0.0017

Table 15 continued

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CONTAINER_SIZE_96	0.007446	0.018599	0.400363	0.6889
CONTAINER_SIZE_101	0.084036	0.013953	6.022642	0.0000
CONTAINER_SIZE_101.4	0.084093	0.012306	6.833261	0.0000
CONTAINER_SIZE_128	-0.295949	0.043727	-6.768137	0.0000
CONTAINER_SIZE_192	-0.043749	0.023322	-1.875886	0.0607
MULTIPACK_2	-0.168744	0.025970	-6.497757	0.0000
MULTIPACK_4	0.315848	0.017266	18.29272	0.0000
JC	0.250494	0.011259	22.24793	0.0000
JC_CKL	0.047220	0.011047	4.274617	0.0000

R-squared	0.753331	Mean dependent var	-3.247204
Adjusted R-squared	0.752828	S.D. dependent var	0.280176
S.E. of regression	0.139293	Akaike info criterion	-1.102398
Sum squared resid	475.8877	Schwarz criterion	-1.085570
Log likelihood	13598.37	Hannan-Quinn criter.	-1.096947
F-statistic	1498.114	Durbin-Watson stat	0.312854
Prob(F-statistic)	0.000000	Wald F-statistic	379.2031
Prob(Wald F-statistic)	0.000000		

Importantly, the estimated coefficient for the labeling claim of “No Sugar Added” is positive, equal to 0.225919 and statistically different from zero. Based on these empirical results, we reject the null hypothesis that the inclusion of the labeling statement “No Sugar Added” has no statistical impact on prices paid by consumers of Brand 1 juice products. In fact, the inclusion of the labeling claim has a substantial positive effect on price per ounce paid by consumers for this product category. As mentioned earlier, the estimated coefficients for the binary variables in the analysis, and in particular the coefficient for the labeling claim, can be interpreted as the percentage change in price of the product as a result of these variables. The actual percentage change in prices is calculated as:

$$[e^{\beta_i} - 1] \times 100$$

where β_i is the estimated coefficient for each dummy or indicator variable. For example, the coefficient for the variable representing whether or not the product bears the ”No Sugar Added” labeling claim is .225919. When applying the above formula to this coefficient, it can be determined that consumers essentially paid a 25.35% premium on the product due to the presence of the “No Sugar Added” claim on the label. As all of the explanatory variables, barring volume, are binary variables, all of the estimated coefficients from Table 15 have been transformed using the aforementioned formula to arrive at percentage changes from the base or reference categories. The resulting percentage changes for the variables relative to their base or reference categories are shown in Table 16.

Table 16: Calculated Percentage Changes Relative to Base or Reference Categories

Variable	Calculated Percentage Change	Variable	Calculated Percentage Change
LOG(OZ_SOLD)	-5.36%	FLAV_CBY_BB	-9.76%
DT	-0.46%	FLAV_CBY_LM	-17.11%
LC	-5.61%	FLAV_CBY_APL	-14.71%
LT	0.61%	FLAV_CBY_STRBY	-9.73%
LABEL_CLAIM	25.35%	FLAV_CBY_TAN	-12.97%
JAN	1.01%	FLAV_WH_CBY	-8.73%
FEB	0.42%	FLAV_WH_CBY_STRBY	-7.28%
MAR	-0.52%	FLAV_WH_CBY_STRBY_GP	-7.35%
APR	0.79%	CONTAINER_PLASTIC	0.86%
MAY	1.79%	CONTAINER_GLASS	4.08%
JUN	0.63%	CONTAINER_SIZE_14	100.04%
JUL	1.50%	CONTAINER_SIZE_16	45.89%
AUG	0.96%	CONTAINER_SIZE_32	114.45%
SEP	0.88%	CONTAINER_SIZE_33.8	2.18%
OCT	0.04%	CONTAINER_SIZE_46	1.85%
NOV	-0.86%	CONTAINER_SIZE_48	5.05%
YEAR_2006	-5.74%	CONTAINER_SIZE_96	0.75%
YEAR_2007	-2.94%	CONTAINER_SIZE_101	8.77%
YEAR_2008	3.34%	CONTAINER_SIZE_101.4	8.77%
YEAR_2009	3.52%	CONTAINER_SIZE_128	-25.62%
YEAR_2010	0.25%	CONTAINER_SIZE_192	-4.28%
FLAV_CBY_GRP	-5.07%	MULTIPACK_2	-15.53%
FLAV_CBY_POM	-6.47%	MULTIPACK_4	37.14%
FLAV_CBY_RP	-6.44%	JC	28.47%
FLAV_WH_CBY_PCH	-3.35%	JC_CKL	4.84%

Base category for the DT, LC, and LT variables—no “light”, “low calorie”, or “diet”
Base category for month—December
Base category for year—2011
Base category for flavor—CBY (cranberry)
Base category for type of container—unspecified
Base category for container size—64 oz
Base category for multipack—single (no multipack)
Base category for JC and JC_CKL—unspecified
Base category for labeling claim—no labeling claim

The subsequent task is to assess damages associated with the claim "No Sugar Added" over the period 2006 to 2011. To carry out this assessment, in our hypothetical case, let's suppose that the manufacturer of Brand 1 is the Defendant. The goal is to determine the extent of ill-gotten profits or sales of this manufacturer (Defendant) associated with the "No Sugar Added" labeling claim. To make this determination, we multiply the respective percentage change attributed to this labeling claim calculated in the hedonic regression (25.35%) by the sum of the corresponding Brand 1 retail sales over the period 2006 to 2011. If information from financial statements of the manufacturer (Defendant) were available, we could obtain the actual sales to wholesalers and retailers over this period; this cumulative sales number subsequently could be multiplied by the premium paid by consumers to arrive at the damages due to consumers in the class action lawsuit. However since access to this information was not available, we instead use the cumulative sum of retail sales available from the Nielsen data for the United States from 2006 to 2011.

In our hypothetical case study, the retail sales for Brand 1 in the period 2006 to 2011, prior to dropping any observations, are $578,801,304; multiplying this figure by the estimated percentage change of 25.35% yields a value of $146,711,157. This figure represents the magnitude of the overpayment made by consumers during the period 2006 to 2011 as a result of the "No Sugar Added" label. If we wish to consider the magnitude of the ill-gotten sales received by the manufacturer of Brand 1, we must take into account the fact that retailers markup prices from manufacturers. As discussed earlier, we noted that the markup is in the range of 20% to 30%. As such, if we subtract out 20%

to 30% from the $146,711,157 figure, then the magnitude of the ill-gotten sales received by Brand 1 is $102,697,810 to $117,368,925, the aggregate damages for the challenged product at issue in this litigation. However, it is important to note that the Nielsen data do not capture all retail sales. As such, the magnitudes of $102.7 million to $117.4 million may be understated. Again, if we had in our possession, the manufacturer's sales of Brand 1 made to distributors and retailers over the period 2006 to 2011, a figure that any company would know, then the magnitude of the damages would be equal to the product of 25.35% times the cumulative sum of their sales.

Because Brand 3 also carried the labeling claim "No Sugar Added", we could have used the same process mentioned previously. For this hypothetical case, we assume that only the manufacturer of Brand 1 is part of the class action lawsuit.

CHAPTER IV

CONCLUSIONS, IMPLICATIONS, AND LIMITATIONS

The principal finding from the hedonic regression analysis of ready-to-drink shelf stable cranberry flavor juices indicated that a statistically significant and positive coefficient exists for the presence of the labeling claim “No Sugar Added” on product packaging. This finding implies that consumers have been paying a significant premium for cranberry flavor juice products as a result of the inclusion of the allegedly misbranded labeling claim. In this specific instance, consumers have overpaid by 25.35% for these products, attributed exclusively to the labeling claim “No Sugar Added”. With this premium, and considering the total sales during the class time period, damages associated with mislabeled Brand 1 products were in the range of $102.7 million to $117.4 million.

Going forward, this methodology could be employed to a wide range of food and beverage products to determine damages due as a result of mislabeled products. The hedonic regression analysis is a methodology employed to determine what price premium consumers pay as a result of the questioned label “No Sugar Added”. But, this methodology could be applied to a variety of label claims such as “No Artificial Flavors,” “All Natural,” “0 Grams Trans Fat,” and many others. A wide and complete body of economic and marketing research has shown that consumers are willing to pay a premium for products bearing many of these characteristics and labeling statements. Additionally, manufacturers would not undertake the costs required in the manufacturing, advertising, and promotion of these products if the benefits of doing so did not outweigh these costs.

The hedonic regression analysis is used to quantify how much of a premium consumers pay for the aspects on the product packaging taking into account other factors that may also affect prices. Simply put, a hedonic analysis involves the specification of a regression with price as a function of a potential myriad of variables, including those accounting for the presence or absence of product attributes represented on labeling claims. Once this premium is determined, the economic damages in class action lawsuits can be calculated. This methodology is not just restricted to the “No Sugar Added” claim, or even to this specific product category of ready-to-drink shelf stable juices featuring the flavor cranberry. It is widely applicable and can be used on different product packaging claims and to a range of product categories in the entire food and beverage industry.

As in any research project, limitations in this analysis are present. With the set of estimated coefficients, omitted variable bias likely was present as the brand explanatory variable had to be dropped to avoid near perfect multicollinearity. However, this issue does not reflect adversely on the model utilized or the subsequent methodology developed in this thesis. As the introduction of hedonic price analysis becomes more prevalent in labeling cases, courts will have to assess the applicability of the method. Consequently, proper model specification will be paramount in the use of this technique in order to capture the premium associated with the labeling claim in question.

Additionally, recall that price, the endogenous variable in the hedonic regression, is defined as the ratio of dollar expenditures divided by quantities sold. Hence by its very construction, volume as an explanatory variable could potentially be endogenous. As such, the estimated coefficients could then be biased. However, based on the Hausman test (1978), endogeneity of the volume variable was not evident in this particular analysis.

In subsequent analyses, the model and methodology are able to be applied if in the data collection process, certain steps are taken. Primarily, in order to avoid collinearity issues, more brands should be included in the analysis. If more brands are utilized, then the high correlation between the brand dummy variables and the labeling claim variable likely would be reduced, permitting the set of brand variables to remain in the regression. Including brand variables will address the omitted variable bias, and more importantly, result in a more precise estimate of the coefficient on the labeling claim variable.

These limitations notwithstanding, as stated by Hartman and Doane (1987, p. 354), “clearly, any analytic technique will be useful if it can assist a court to certify the class by explicitly determining whether class members were commonly and uniformly damaged by Defendant's illegal actions. Hedonic regression analysis is such a technique. Using it, the court can focus on the action(s) of the Defendant and measure the common damage to each putative class member. Depending on the specific statute violated, the damages will reveal themselves in such observable economic measures as product prices…” To this end, a hypothetical case study example involving ready to drink cranberry juice products was developed and presented illustrating the use of the hedonic regression technique.

REFERENCES

Abere, A., 2010. “Using Economics to Measure Damages in Private Advertising Litigation,” *The Adviser*, 1(1):14-17.

Anstine, J., 2007. “Organic and All Natural: Do Consumers Know the Difference?” *Journal of Applied Economics and Policy*, 26(1):15-27.

Balasubramanian, S. K., and C. Cole, 2002. “Consumers’ Search and Use of Nutrition Information: The Challenge and Promise of the Nutrition Labeling and Education Act,” *Journal of Marketing*, 66(3):112-127.

Choiniere, C.J. and A. M. Lando, 2010. 2008 Health and Diet Survey. http://www.fda.gov/Food/FoodScienceResearch/ConsumerBehaviorResearch/ucm193895.htm#FOODLABELUSEALL.

Combris, P., S. Lecocq, and M. Visser, 1997. “Estimation of a Hedonic Price Equation for Bordeaux Wine: Does Quality Matter?” *The Economic Journal*, 107(441):390-402.

Court, A.T., 1939. “Hedonic Price Indexes with Automobile Examples,” The Dynamics of Automobile Demand, New York: The General Motors Corporation.

Feenstra, R.C. and M.D. Shapiro, ed., 2003. *Scanner Data and Price Indexes*, National Bureau of Economic Research: Studies in Income and Wealth

Hartman, R. S. and M. J. Doane, 1987. “The Use of Hedonic Analysis for Certification and Damage Calculations in Class Action Complaints,” *Journal of Law, Economics, & Organization*, 3(2):351-372.

Hirogaki, M., 2013. “Estimating Consumers’ Willingness to Pay for Health Food Claims: A Conjoint Analysis,” *International Journal of Innovation, Management, and Technology*, 4(6):541-546.

Hottman, C., 2014. “Retail Markups, Misallocation, and Store Variety in the US” Job Market Paper, Department of Economics, Columbia University.

Jain, S. “Using Hedonic Price Analysis in Food Labeling Class Actions,” *Law360*, June 8, 2015.

Kim, S.-Y., R.M. Nayga, Jr., and O. Capps, Jr., 2000. “The Effect of Food Label Use on Nutrient Intakes: An Endogenous Switching Regression Analysis,” *Journal of Agricultural and Resource Economics*, 25(1):251-231.

Li, J. and N.H. Hooker, 2009. “Documenting Food Safety Claims and Their Influence on Product Prices,” *Agricultural and Resource Economics Review*, 38(3):311-322.

Maguire, K., N. Owens, and N. B. Simon, 2004. “The Price Premium for Organic Baby Food: A Hedonic Analysis,”, *Journal of Agricultural and Resource Economics* 29(1):132-149.

Markosyan, A., T. I. Wahl, and J. J. McCluskey, 2007. “Functional Foods in the Marketplace: Willingness to Pay for Apples Enriched with Antioxidants,” Selected Paper Prepared for Presentation at the AAEA Annual Meeting, Portland, OR.

Mayen, P. D., 2013. “Influence of Antioxidant Information on Consumer Preference for Tree Nuts,” Working Paper, New Mexico State University.

Moro, D., P. Sckokai, and M. Veneziani, 2012. “Consumers’ Willingness to Pay for a Functional Food,” Paper Prepared for Presentation at the 1st AIEAA Conference, Towards a Sustainable Bio-Economy: Economic Issues and Policy Challenges.

Miskolci, S., 2011. “Consumer Preferences and Willingness to Pay for the Health Aspects of Food,” Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis, 54(4):167-175.

Muth, M.K., C. Zhen, J. Taylor, S. Cates, K. Kosa, D. Zorn, and C. Choiniere, 2013. “The Value to Consumers of Health Labeling Statements on Breakfast Foods and Cereals,” *Journal of Food Products Marketing*, 19(4):279-298.

Nerlove, M., 1995. “Hedonic Price Functions and the Measurement of Preferences: The Case of Swedish Wine Consumers,” *European Economic Review*, 39(9):1697-1716.

Newey, W. K. and K. D. West, 1987. “A Simple, Positive Semi-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix,” *Econometrica*, (55)3:703-708.

Nielsen, A. 2012. 2012 Nielsen Retail Scanner Data. Chicago, IL. https://research.chicagobooth.edu/nielsen/.

Rosen, S., 1974. “Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition,” *The Journal of Political Economy*, 82(1):34-55.

Rubinfeld, D. L., 2000. “Reference Guide on Multiple Regression,” in Federal Judicial Center, Reference Manual on Scientific Evidence, pp. 179-227.

Russo, J. E., R. Staelin, Nolan, C. A., Russel, G. J., and Metcalf, B.L. 1986. “Nutrition Information in the Supermarket,” *Journal of Consumer Research*, 13(1):48-70.

Satimanon, T., and D. Weatherspoon, 2010. "Hedonic Analysis of Sustainable Food Products," *International Food and Agribusiness Management Review*, 13(4):57-74.

Steiner, B, 2004. "Australian Wines in the British Wine Market: A Hedonic Price Analysis," *Agribusiness*, 20(3): 287-307.

U.S. Food and Drug Administration, 2007 Guidance for Industry: Dear Manufacturer Letter Regarding Sugar Free Claims. http://www.fda.gov/RegulatoryInformation/ Guidances /ucm053431.htm

U.S. Food and Drug Administration, 2009 Guidance for Industry: Letter Regarding Point of Purchase Food Labeling. http://www.fda.gov/Food/GuidanceRegulation/ GuidanceDocumentsRegulatoryInformation/LabelingNutrition/ucm187208.htm.

U.S. Food and Drug Administration, 2013. Food Labeling Guide. http://www.fda.gov /Food/GuidanceRegulation/GuidanceDocumentsRegulatoryInformation/LabelingNutrition/ucm2006828.htm.

U.S. Food and Drug Administration, 2014. Code of Federal Regulations. 21 CFR 101, Food Labeling. http://www.accessdata.fda.gov/scripts/cdrh/cfdocs/cfcfr/cfrsearch .cfm?fr= 101.60.

Waugh, F.V., 1928. "Quality Factors Influencing Vegetable Prices," *Journal of Farm Economics*, 10(2):185-196.

Xiao, J. 2012. "A Hedonic Analysis of Retail Milk and Oatmeal Attributes in Quebec" Department of Agricultural Economics, McGill University, Montreal.